



Historic networks and commemoration: Connections created through museum exhibitions

L.E.A. Braden^{a,*}, Thomas Teekens^b

^a Arts and Culture Studies, Erasmus School of History, Culture, and Communication, Erasmus University Rotterdam, The Netherlands

^b Department of Sociology, Faculty of Behavioural and Social Sciences, University of Groningen, The Netherlands

ABSTRACT

This research examines how contextualization of artists within historical cohort networks affects art historical commemoration. Examining a population of 236 artists who first exhibited between 1946 and 1955 in three of the Netherlands' largest museums (Boijmans, Stedelijk, and Van Abbemuseum), we examine the cohort connections curators create for these artists through exhibition and analyse how such connections affect historical commemoration. We argue a "historic network" is created through museum exhibitions, where exhibitions position artists within history. Employing network analysis, we examine exhibition connections established for artists with prior (1930–1945), concurrent (1946–1955), and subsequent artist cohorts (1956–1989)—altogether examining connections across 317 exhibitions and analysing a network of 4 428 individual artists. Using sequence analysis, we show when historic cohort networks are employed within exhibition and how these networks evolve over time. Next, we examine which type of networks receive the greatest art historical commemoration. Our findings indicate those artists with the most consistent and coherent networks are far more likely to be recognized and remembered. We argue because history is presented relationally, those artists with overarching historic cohort connections fit more easily into a historical narrative, leading to a greater likelihood of being commemorated over time. Overall, the research introduces the idea of historic cohort networks to provide an analysis of how museum exhibitions contextualize artists within history and affect art history and commemoration.

1. Introduction

When artists' works are shown together in museum exhibition, a connection between these artists is created in the mind of, first, the curator and then the audience. In aggregate, these exhibition connections can be envisioned as a network between exhibited artists, created by curators and used by audiences to understand artistic and historical context and significance. In this research, we examine the networks created when artists are exhibited together and how these networks affect long-term commemoration. Consequently, rather than engaging the personal, actor-created elements of connections (e.g., friendship, collaboration, mentorship), this research focuses on connections which associate artists conceptually. We argue, conceptual connections created between artists can, among other things, serve to historically contextualize the artist. Because exhibitions advocate a meaningful association between artists (literally presenting artists side-by-side), we argue exhibitions can conceptually link artists with those who worked before, concurrent with, or after the artist. In this way exhibition networks may function to position artists within art history and, consequently, increase the artist's chance at historical commemoration.

The research engages three innovative objectives. First, we consider the effect of networks created between generational cohorts, where connections are made between an artist and those peers who came chronologically before and after. We argue such connections create a fabric of history which contextualizes historical personages and weaves together their connection to one another over time. Consequently, not only do connections help explain an individual's place in history, but connections help us comprehend the character and function of a temporal sequence by demonstrating how historic people aided in progressing history's narrative to

* Corresponding author.

E-mail addresses: Braden@eshcc.eur.nl (L.E.A. Braden), t.p.teekens@rug.nl (T. Teekens).

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the present-day (Griffin, 1993; Iggers, 2005).

History's progression narrative is particularly evident in art history, where artists are often associated or grouped together (e.g., "movements") and these collectives are directly linked to former and subsequent groups through a line of artistic influence. Associations across generations connect artists through time in order to provide an account of "how a steady line of development has led inevitably from those beginnings to the present situation of undoubted achievement" (Becker, 1982:346). For example, the table of contents of most major art history textbooks move chronologically, organizing history through progressive artistic groupings. Likewise, museum collections are commonly organized according to time periods, which move from past to present work in order to delineate influence and show "progression".

Our second objective is to offer a mechanism behind commemoration by observing how institutional activities (i.e., museum exhibitions) create historic placement. Because institutions structure cultural meaning (Douglas, 1986), when and how historical personages are positioned and presented together within a cultural institution articulates a conception of history. This conception in turn structures the basis of cultural knowledge, such as through biographies, historical accounts, and textbooks. By discerning how institutions generate historical connections over extended periods, this research seeks a greater understanding of how, at least one way in which, institutions signal who should be commemorated.

Third, in a larger, general proposition, we understand historical networks as a type of symbolic network. We argue when a network is formed not by actor-created connections, but by others that associate actors with one another, this creates a "symbolic network" which has particular import for reputation development (see Braden, 2018). While emphasis is usually placed on the actor's efforts, reputation is fundamentally a social phenomenon—an evolving attribute assessed and ascribed to the actor by others (for a discussion on reputation, Braden and Teekens, 2019). In this way, the importance of symbolic networks is particularly evident in long-term and historic reputation building: whereas social connections are grounded in immediate, physical proximity (such as friendships, collaborations, etc.), reputational connections are often made outside personal contacts and beyond the lifetime of the historical personage. For example, consider the reputational argument of comparing the presidency of Donald Trump to Richard Nixon's, or the customary grouping of Mozart, Beethoven, and Bach. In this understanding, symbolic associations drive reputational understanding of an actor—and, while "actor" denotes agency, reputation can be affected without first-person connection (Giuffre, 1999). If reputation is not simply the product of what people think about an actor, but rather how the actor is known (Granovetter, 2005), we argue, over time, aggregate symbolic associations form a network by which the actor is culturally understood.

We begin by introducing the concept of historic networks, offering an idea of how this concept may expand work already done in the field of reputation-building.

2. Historic networks

Reputational development by others on behalf of an actor is particularly evident in the long-term, for example, when actors garner posthumous prestige and attention. Acting as "reputational entrepreneurs" (Fine, 1996), others may work to shape how later generations understand an actor. When developing historic understandings about an actor, association is a fundamental tool for reputational entrepreneurs. Schwartz (1991) describes the modern formation of George Washington's reputation as partially reliant on historians comparing Washington with other successful presidents, especially Abraham Lincoln. Corse and Griffin (1997) cite Alice Walker's 1983 self-created and promoted connection to the 1930's writer Zora Neal Hurston as central to Hurston's re-discovery and commemoration. Research on music evaluation often highlights the importance of critics who draw associations between established and emerging performers as a legitimating strategy for the lesser-known artist (see Schmutz and Faupel, 2010; Venrooij and Schmutz, 2010), while Wohl (2019) details how even established visual artists attempt to create connections to previous work of importance. Both Bielby and Bielby (1994) and Franssen and Kuipers (2013) also highlight the importance of associations, indicating media gatekeepers legitimize financing decisions based on rhetorical strategies of comparison. For example, new products and producers "in the tradition of" established works are more likely to be picked up by both TV executives and book editors.

Such research illustrates the way associations between artists shape cultural perception and signal an actor's importance. Within this research we distinguish two central premises: first, meaningful associations can be based on conceptual connections (e.g., comparison, correspondence, (dis-)association) rather than actor-directed affiliation (mentorship, collaboration, friendship). Second, such connections can be created by others, rather than the actor, to establish and strengthen reputational commemoration.

Building from prior research, we are interested in looking beyond specific, individual connections. Rather, we wish to examine broad networks that historically contextualize. Our premise is that actors associated with successive historical cohorts are better recognized within art history, serving as a bridge between previous and subsequent generations and as representative of their own cohort and time. Placement is important for commemoration as it demonstrates the actor's historical relevancy, as he or she proceeds from former cohorts and cedes to subsequent. While individual connections are important and often celebrated, general historic connections lay a greater foundation for an artist's context. Giuffre (2001) explicates this idea through her conception of "mental maps," where a photographer's style is categorized by critical evaluation, rather than defined by the artist. Successful artists are those best "fitted" into a broad scope of categories, enabling critics to associate these photographers with a wide variety of styles. Likewise, Giuffre's previous work (1999) demonstrates that photographers with broad, weak connections to a range of artists and galleries result in the greatest critical attention. We wish to extend this idea of mental maps to historic understandings of an artist, examining how broad associations serve to categorize artists within art history.

Rather than focusing on an individual reputational entrepreneur, such as a specific historian or curator, we are interested in institutional positioning. We try to capture more than the efforts of one or two people by examining three different museums over 60

years. Moreover, in selecting our data from the Netherlands, a geographically concentrated nation, we develop a good cross-section of museums within a central European country. Finally, since museums are created for long-term, sustained reputational advocacy and the broad distribution of this advocacy to the larger public, we believe museums serve as ideal institutions by which to explore the effect of historic networks on larger cultural knowledge.

Understanding historic networks also requires capturing the development of connections over time. Indeed, the ability to evolve connections is an essential component of how a historical figure is understood (Mead, 1929; Maines, Sugrue, and Katovich, 1983). Lang and Lang (1988) find historical contextualization is sensitive to different connections at different points in an actor's reputational career. For example, when an actor's reputational standing is weak, connections to past actors may serve to endorse and substantiate reputation. Conversely, a strong but stale reputation may rejuvenate when connected to the up-and-coming generation.

In this research, we focus on museum exhibitions. While there are several reasons why objects are exhibited collectively, the core idea behind exhibition is, together, objects demonstrate associations which make them more artistically or educationally meaningful (Dean, 1996). An essential component of exhibition, then, is to instruct the audience on why objects were selected and how they fit together collectively. Such instruction can be explicit through the title of the exhibition and catalogue text, labels for the pieces exhibited, promotion materials, and other supporting content; however, implicitly, simply exhibiting works together asserts comparability and association, creating a conceptual connection not just between artworks, but also between artists. These associations are made clear in group exhibitions, where the connection between the artists is the focus. For example, exhibitions such as “*Cézanne, Gauguin, Seurat, Van Gogh*,” “*Ad Reinhardt and Mark Rothko*,” or “*Stieglitz, Weston, Adams, and Callahan*”¹ clearly conceptually link these artists. By showing artists together, exhibitions create a deliberate grouping and advocate a symbolic connection. Take the exhibition “*Wegbereiders van het modernisme/Pioneers of modernism: Ensor, Holderm Kruyder, Munch*”² where curators consciously acknowledge their creation of a symbolic connection between the exhibited artists:

The combination of James Ensor (Belgium, 1860–1949), Ferdinand Holder (Switzerland, 1853–1918), Herman Kruyder (Netherlands, 1881–1935), and Edvard Munch (Norway, 1863–1944) within a single exhibition is a deliberate choice. Although these four separate artists, who scarcely knew each other, if at all, they have a great deal in common not only stylistically—an obvious Symbolist and Expressionist disposition is to be seen in their paintings—but also in terms of imagination, intention, and inspiration (from the exhibition catalogue, Schampers, 1988:12).

We argue such exhibition connections also serve to position artists within history by demonstrating how (or, more accurately, with whom) artists link across successive cohorts. Such connections are intended to communicate to the broader public intellectual connections between actors, as well as provide a narrative for the current state and progression of the field (i.e., how past, present, and emergent actors correspond). In this way, established connections become part of our shared understanding of how art progresses as history (Fine, 1996; Halbwachs, 1992).

3. Data

3.1. Research population

In examining historic connections, we consider it important to create a universe of connections rather than selecting a sample. While previous research has shown the qualitative importance of specific, often celebrated connections (e.g., Corse and Griffin 1997; Farrell, 2003; Jones, 2010), we concentrate on the totality of connections created in order to understand each artist's aggregate and evolving network over time. Again, these networks are symbolic, where artists are purposely exhibited together to show a conceptual relationship. To understand the conceptual framework of a symbolic network, we must capture “successful” repeated connections, as well as those made rarely and then discontinued.

We utilize a cohort of 236 artists for our research. This cohort represents all artists first exhibited in three major Dutch museums between 1945 and 1954. We choose the cohort of artists emerging after WWII to avoid the problematic censure of artistic exhibition during wartime, as well as to capitalize on the surge of post-war artists who emerged in Europe (Hopkins, 2000). To re-establish the art world context for returning audiences, curators in this decade were careful to historically contextualize emerging artists within exhibition (Hopkins, 2000), consequently providing an ideal cohort for exploring historical connections.

To provide a cross-section of the Dutch museum environment, we examine exhibitions from the Museum Boijmans van Beuningen in Rotterdam, Stedelijk Museum in Amsterdam, and Van Abbemuseum in Eindhoven. The Stedelijk and Van Abbemuseum specialize in modern art (~1850-present), while Museum Boijmans serves as a general museum, displaying historic to avant-garde visual art. We define an “exhibition” as temporary museum programming, designed around specific theme and content. While artworks from a museum's collection can be part of the exhibition, works shown concurrently but outside the exhibition programme (such as part of the museum's permanent display) are not part of our data. We are defining exhibition connections by the symbolic link created when artists' work(s) are presented together in an exhibition; additional exhibition connections create a repeat and, consequently, stronger tie. We argue that in-common exhibition with other artists creates a network of exhibition connections which is the main focus of our research. Our next step documents every artist who exhibited with our cohort from 1945 to 1989 in the three museums. In total, our data population contains 317 exhibitions and a network of 4 428 artists.

¹ Museum of Modern Art (NY) exhibitions #1 (1929), #2035 (2008), and #1858 (2000), respectively.

² Museum Boijmans van Beuningen (Rotterdam), exhibition 18 December 1988 – 12 February 1989

3.2. Locating types of historic connections

Our research requires a methodology that recognizes both symbolic placement and temporal flow. Therefore, we employ a combination of social network and sequence analysis to track how artists are connected through museum exhibitions, and how these historic connections evolve over time. This twofold methodology is necessary to capture the interplay between historical network positioning and commemoration. Overall, we want to elucidate which historical networks will solidify over time, and what networks fail to create a consistent position.

Our population of artists from the three museums ($N = 4\,428$) is divided into broad historical cohorts: those artists who were exhibited before our reference population (“past”), those part of our reference population (“present”), and those who exhibited after the emergence of our reference population (“future”). As discussed above, we define a specific cohort of artists as our reference or “present” artists. These are all artists emerging in three major Dutch museums between 1945 and 1954 ($N = 1\,240$)³. The other divisions are defined relative to this “present” cohort of artists. For example, “past” artists ($N = 536$) are those who exhibited with our present cohort, but also proceeded this cohort by exhibiting in the museum before 1945; “future” artists first exhibited after 1954 ($N = 2\,652$)⁴. Future artists are “future” to our “present” cohort in that these artists debuted in the museums after our research cohort first exhibited. Here, we argue an artist’s first exhibition in a museum serves as a measure of when the artist’s institutional reputation began and, therefore, when the artist’s career within the institution is positioned historically. While some artists may have started creating art long before a museum exhibited their work, this research still groups the artist in cohorts according to when they first exhibited. Again, we are not examining the individual artist’s careers or histories, but rather the institution’s recognition, positioning and connections of these artists⁵. To allow for longitudinal analysis of career trajectories, we divide our timeline into nine five-year periods between 1945 and 1989 (1945–1949, 1950–1954, 1955–1959, etc.). Slicing the timeframe into nine periods allows for a detailed analysis of historical change while leaving room for interpretable results⁶. Once we determine the artists with whom our population exhibited, for each five-year period, we calculate the number of connections (or “ties”) an artist has with those who exhibited before (prior to 1945), within their cohort (1945–1954), and subsequently (1955–1989).

Fig. 1 offers an illustration of a five-year network of exhibition connections and the different categorizations possible. In complement, Table 1 provides the parameters for assessment of specific scores. Artists who occupy a structurally equivalent network position (White, Boorman and Breiger 1976) are given the same score. In Table 1, scoring an “A” indicates an artist is strongly exhibited with all historical cohorts; that is, relative to other artists, this artist has many connections with “past,” “present,” and “future” artists in this five-year period. Scoring an “F” indicates, during this five-year period, an artist is largely connected to artists from his/her own cohort and was rarely exhibited with artists from past or future cohorts. The score of “H” is given to artists exhibited during this period, but who were not connected strongly to any of the cohorts. The last category “X” is assigned to artists not exhibited in the three museums during a given five-years⁷. In Appendix A, we detail how we define each of these connections.

For each five-year interval, an artist was assigned one of the scores given above so that, chronologically ordered, an artist’s nine scores show her or his historic network movement through time. That is, the scores form a sequence that indicates at what point these artists were more connected to their own cohort, “past” artists, and when “future” artists became salient and associated. Assigning each artist a score in time results in a varying array of sequences. From the 236 artists in our cohort, 165 different trajectories emerge. Such large variety in trajectories is not surprising, considering “the number of possible careers surpasses calculability” (Abbott and Hrycak 1990:144). Nevertheless, it is possible to reduce the amount of variation in sequences through Optimal Matching (OM) methods (see Abbott and Tsay 2000). Through this OM algorithm, we can group together those artists whose sequences are most similar. For the technical specifications of our Optimal Matching algorithm, please see Appendix B.

³ For the longitudinal analysis required for capturing evolving networks, we subsequently narrowed our population of artists first exhibited between 1945 and 1954 to those who exhibited three times or more in our total timeframe. This reduced the research population from 1 240 to 236 artists.

⁴ Intuitively, the cohorts’ differing sizes seem disproportional. However, empirically we find the contrasting number of artists assigned to the future cohort ($N=2\,652$) as opposed to the past cohort ($N=536$) does not affect historic positions in proportion. The “future” cohort naturally contains more ephemeral exhibitors (only 687 artists of this cohort exhibited more than once), as opposed to the “past” cohort of artists who have sustained through time and exhibited more frequently. Consequently, for our research, “past” artist’s significance in exhibition networks is stronger per individual artist. The ostensible disparity in the population distribution is further disproved in our findings, as exhibition connections with past artists appear roughly as much as those with future artists.

⁵ Note, for the first two time periods (1945–1949; 1950–1954), options A, C, D and G do not occur, as the “future” artist category has yet to come into existence.

⁶ Using smaller time periods yielded similar results, indicating robustness. However, given the amount of data, we chose five-year periods for ease of interpretation.

⁷ A reasonable question is whether the networks created through museum exhibition in three different museums can actually be aggregated without losing information on their individual contents. To assess whether the networks created in our three different museums differ significantly, we performed a Quadratic Analysis Procedure (Borgatti, Everett and Johnson 2013). Such a test allows to check for correlations within inter-dependent structures, such as networks. Results from these tests indicate the exhibition networks between museums correlate significantly ($p < 0.001$) with each other. Results of the QAP analyses can be requested from the authors.

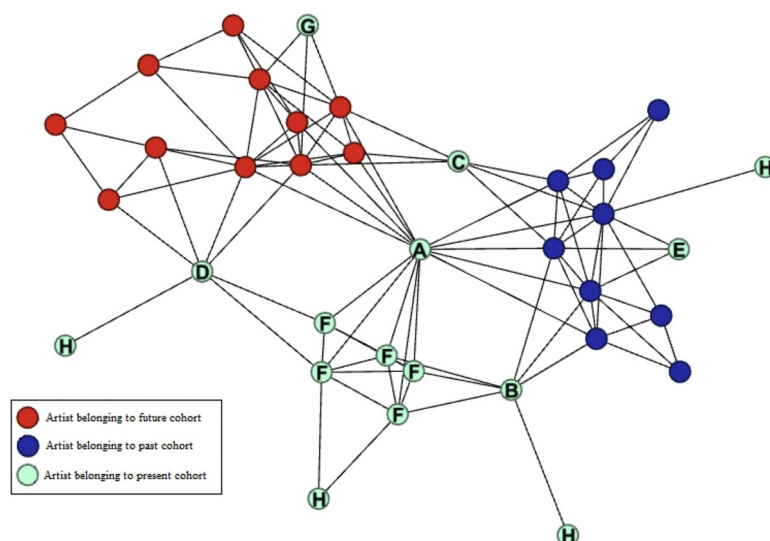


Fig. 1. An illustration of an exhibition network with score assessments

Table 1

Parameters for exhibition network position assignment

Network position	Past	Present	Future
A	strong	strong	Strong
B	strong	strong	<
C	strong	<	Strong
D	<	strong	Strong
E	strong	<	<
F	<	strong	<
G	<	<	Strong
H	<	<	<
X	0	0	0

4. Results: five types of historic networks

Our analysis reveals five typical sequences of artists' historic networks over time, as seen in Fig. 2. For illustration, Table 2 provides example sequences for each type and, in the following section, we detail the trajectory of each of the five aggregate network sequences found.

4.1. Sequence 1: bridges

Exhibition connections for artists in Sequence 1 are generally robust throughout the timeframe. Though their emergence is largely marked by modest connections, by 1955 these artists are increasingly exhibited with a range of artists from all cohorts: past, present, and future. Between 1965 and 1969, there is a shifting moment in their historic network connections; the artists belonging to this sequence strongly connect to their own cohort in these years and, afterwards, they become strongly connected to all cohorts (past, own, and future) for the remainder of the timeframe.

A select group of artists fits Sequence 1. While a relatively small group (six artists), their historic networks are markedly different from other artists in their 1945–1954 cohort. Particularly, the period 1965–1969 shows a distinct shift in thinking about this group. In this five-year segment, curators seem to place these artists within their historical period by exhibiting them with those from their historical peer-group (1945–1954). After a strong positioning within their own peer-group, the artists are then exhibited with a wide-range of cohorts of prior, contemporary, and subsequent artists. Given Sequence 1 artists are some of the most well-connected within our research cohort, the strong peer connections during 1965–1969 may indicate the grounding of these artists within their own historical cohort, allowing curators to establish these artists as representatives of their time. Subsequently, curators may have used these “established” artists as benchmarks of comparison within exhibitions which brought together a wide range of artistic periods. Alternatively, curators could be signaling these artists as particularly well-suited for bridging artists from different periods. Whatever the intention, these artists are exhibited with a range of historical connections, serving to historically situate and contextualize them.

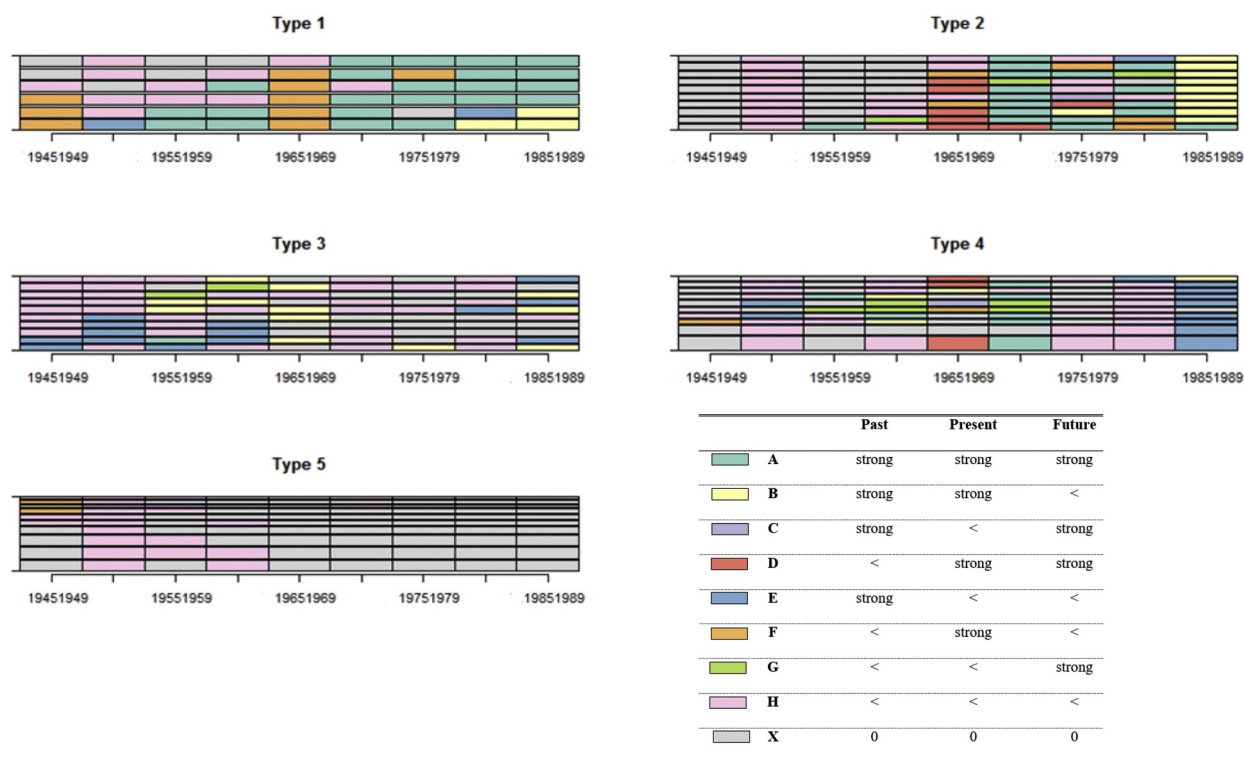


Fig. 2. Five types of historic network sequences found in exhibition from 1945 to 1989

Table 2

Exemplary artists per sequence type

Name	45-49	50-54	55-59	60-64	65-69	70-74	75-79	80-84	85-89	Sequence type	Characterization
Karel Appel	F	E	A	A	F	A	A	B	B	1	Bridges
Joseph Beuys	X	H	X	H	F	A	D	A	B	2	Slow-starters
Pierre Alechinsky	X	H	H	G	H	E	H	H	E	3	Retrospective
Jaap Wagemaker	F	H	H	B	X	A	X	H	E	4	Sporadic
Wally Elenbaas	H	H	H	H	H	X	X	X	X	5	Ephemeral

4.2. Sequence 2: slow-starters

The artists who compose Sequence 2 can be described as slow-starters. Debuting between 1950 and 1954, initially these artists are rarely exhibited and, when they are, weakly connected with past and their own cohorts. Much like Sequence 1, these artists experience a surge of strong connections, albeit five years later (1970–1974) and to all cohorts of artists: past, peer, and those who debuted subsequently. After 1975, these artists are established and exhibit consistently, but without a consistent pattern of connections. In the final period of our timeframe (1985–1989), this sequence changes to majority “B” score, designating strong relations to both past and peer cohort artists.

In comparison with Sequence 1, Sequence 2 artists are seemingly never grounded within a historical period. By 1965, these artists begin to exhibit steadily, yet without lasting connections to any generation. Possibly Sequence 2’s lack of grounding within a historical grouping works to destabilize them within the historical narrative, where curators struggled to find lasting connections through which to position these artists.

4.3. Sequence 3: retrospective

Artists ascribed to Sequence 3 are marked by both relatively continuous exhibition throughout the timeframe and their connection to past cohorts. In the first decade of exhibitions, these artists emerge connected to older artistic generations and to those of their own cohort. This pattern of connections remains fairly consistent throughout the timeframe, though these artists experience intermittent five-year periods without exhibition from 1965 to 1989. Overall, Sequence 3 artists are distinguished in their historic networks by periods of strong connection to older generations, particularly during the first decades of these artists’ appearance in exhibition (1945–1964) and, then again, towards the end of the timeframe (1980–1989).

4.4. Sequence 4: sporadic

The artists of Sequence 4 exhibit irregularly and are marked by inconsistent connections to a wide variety of artistic periods. Typical of this sequence's historic networks are changeability and lack of uniformity in connections. Artists are intermittently strongly connected to present and future cohorts (1965–1969), then to all cohorts (1970–1974), and end with majority connections to their predecessors (1985–89). Though they are increasingly exhibited over the timespan of this research (1945–1989), these artists seem unable to secure connections and, therefore, arguably fail to secure placement in any art historical narrative. Artists of this sequence seem shuffled through history: the moment they are strongly exhibited with one historical cohort, they are refitted into other historical contexts.

4.5. Sequence 5: ephemeral

Not all museum exhibited artists achieve lasting exposure. Artists of Sequence 5, by far the largest group of artists, exhibited in the three museums from 1945 until approximately 1964, and then are not featured again for the remainder of the timeframe. As these artists do not achieve either strong or lasting connections with any specific cohort, the reputations of such artists, we argue, fail to resonate with any art historical narrative and are consequently jettisoned from exhibition.

5. The effect of historic networks on commemoration

5.1. Books as indicators of historical commemoration

After identifying the major types of historic networks, we wanted to understand how each type perform regarding long-term commemoration. Historical commemoration is measured here by tracking the number of books and monographs written about each artist. Books are important mediums for commemoration and serve as indicators of cultural consecration (Braden, 2009; Verboord, 2003). For each artist, we record the number of books written about the artist from the library of the Netherlands Institute for Art History (RKD), a government-funded archive that aims to create an overview of Western art history. RKD has an additional benefit of structuring their database on books dedicated or partially dedicated to a specific artist, rather than listing all books with tangential reference to an artist.

5.2. Intervening variables: nationality, birth year, solo exhibition, exhibition size, and repeat ties

Considering our dataset consists of exhibitions in Dutch museums, entrance into exhibition is likely easier for Dutch artists. International artists, on the other hand, already acquired at least some fame before being exhibited in a foreign (Dutch) museum (Quemin, 2006). Given a likely oversupply of Dutch artists and the probable advanced reputation of foreign artists, we hypothesize Dutch nationality will have a negative effect on historical commemoration. To control for this possible effect, we include a variable for Dutch origin in our analysis.

Another personal characteristic of an artist we include in the model is the artist's birth year. As we are particularly dealing with the theoretical connection between artist's cohorts, literature indicates an important predictor for success may be an artist's age (Galenson, 2009; Accominotti, 2009). We include the variable birth year in the analysis to make sure the variation in our sample is not explained by differing ages, either because of a longer "incubation period" for older artists (i.e., those who have lived longer have had more opportunity for recognition) or because a specific period garners more art historical attention.

Third, we consider the alternative hypothesis that individual success of the artist alone drives her or his commemoration. To test this alternative, we measure the number of solo exhibitions given to an artist in the three museums. As museum solo exhibitions are the highest indicator of a visual artist's consecration (Becker, 1982), we expect solo exhibitions to positively affect an artist's historical commemoration. Additionally, including solo exhibitions into our analysis as a control variable helps distinguish the effects of individual recognition from network influence.

Fourth, we control for exhibition size. A possible alternative hypothesis is that an exhibition's exclusivity helps determine future commemoration. In other words, if only a few artists are highlighted in an exhibition, such focused attention aids the historical commemoration of the artists. We control for this alternative cause by including the average exhibition size in which artists appeared.

Finally, we add the intervening variable of an artist's repeated ties in museum exhibitions to our analysis. That is, we test the alternative hypothesis that artists are consistently connected to the same others, with the repetition of connections in itself leading to greater commemoration. By including this control variable, we want to examine whether placement within general historical networks or the reoccurrence of specific connections has greater impact on an artist's commemoration. Consequently, we distinguish the strength of specific ties from an artist's position in a historical network, using the percentage of repeated ties compared to total ties as a measurement.

6. Results

OLS regression analysis is used to determine whether artists with different historic network types achieve different levels of historical commemoration. Table 3 shows the results of our analyses.

As Table 3 demonstrates, artists belonging to different historic network types achieve different levels of historical

Table 3OLS Regression results on book inclusion. Values are β standardized effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sequence							
Type 1	0.470***	0.507***	0.518***	0.245***	0.475**	0.430***	0.326***
Type 2	0.198***	0.197***	0.277***	-0.015	0.211***	0.151**	0.065
Type 3	0.375***	0.370***	0.370***	0.248***	0.382***	0.330***	0.248***
Type 4	0.092	0.061	0.190**	-0.045	0.113	0.063	0.029
Type 5	reference category						
Control variables							
Nationality		-0.191***					-0.175**
Birth year			-0.277***				-0.216***
Solo exhibition				0.457***			0.442***
Exhibition size					-0.045		-0.056
Repeat ties						0.165**	0.017
r^2	0.348	0.382	0.409	0.453	0.350	0.370	0.532

***= $p < 0.001$, **= $p < 0.01$, *= $p < 0.05$

commemoration, even when controlling for the alternative predictors Dutch nationality, birth year, exhibition size, and repeat ties. Model 1 predicts the number of books about an artist by taking solely the effects of sequence. Here, the variable “Sequence” was turned into a dummy variable, with Sequence 5 (“ephemeral”) as the comparison group. Effectively, this first model shows the significant differences between artists belonging to different groups, without controlling for other effects. This model already captures much variance found in the historical commemoration of artists, as only this dummy variable already accounts for 34.8% of found variance ($r^2 = 0.348$). Before turning to an interpretation of the coefficients of each sequence group in comparison to Sequence 5, we next discuss the effects of our included control variables.

Models 2 through 6 include the effects of our control variables. Here we find four out of five of our alternative hypotheses are initially confirmed. Both solo exhibitions and repeat ties have a positive significant effect on historical commemoration, whereas Dutch nationality and an artist's birth year have a negative effect, where the negative effect of an artist's birth year indicates that the earlier the artist is born, the higher the amount of books about the artist are in the RKD library. Exhibition size does not achieve significance. Two additional insights appear in these models. First, when controlling for birth year in Model 3, the difference between artists in Sequence 4 (“sporadic”) and 5 (“ephemeral”) becomes significant. While there is no significant age difference between the sequences, the older artists of Sequence 4 are the focus of more books than the artists of the same age in Sequence 5. Second, controlling for solo exhibition in the museums during our timeframe in Model 4 allows for the difference between Sequence 2 (“slow-starters”) and 5 to turn insignificant (also in the final model). This indicates the difference between Sequences 2 and 5 found initially is not necessarily explained by their sequence of exhibition networks, but rather by solo exhibition.

The final model, Model 7, contains all variables and continues to indicate a significant effect of network type on the number of books written about an artist, even after controlling for the five covariates. As such, in spite of the large effect of solo exhibitions on historical commemoration ($\beta = 0.442$, $p < 0.001$) and the smaller, yet still significant effects of birth year ($\beta = -0.216$, $p < 0.001$) and Dutch nationality ($\beta = -0.195$, $p < 0.01$), artists with different historic networks achieve different levels of commemoration. The intervening variables of average exhibition size and repeat ties lose their effect in this inclusive model. Overall, Model 7 predicts 53% of the found variance ($r^2 = 0.532$).

Next, we detail how artist recognition within books differs between sequences using the results from our analysis in Model 7. Table 4 offers a short descriptive summary. Artists of Sequence 1 (“bridges”) score by far the highest, with a mean of almost 96 books per person. These results indicate those artists who were consistently exhibited with past, present, and future artists are most recognized within art historical books. The second most commemorated artists belong to Sequence 3 (“retrospective”). These artists garner more than 47 books on average, notably outperforming the remaining sequences (artists from Sequence 2 have an average of 34 books, Sequence 4 have 21.75 books, and Sequence 5 have approximately 14 books). As the variables in Model 5 show, after controlling for Dutch nationality, solo exhibition, birth year, exhibition size, and repeat ties, artists belonging to Sequence 2, 4, and 5 do not reach significantly different numbers of books.

Overall, we find different types of historic networks affect commemoration in different gradations—though, in support of our hypotheses, we find those artists with exhibition networks of past, present, and future artists garner the greatest textual recognition.

Table 4

Book inclusion means per sequence type

Sequence	Mean
Type 1	95.67
Type 2	34.22
Type 3	47.20
Type 4	21.74
Type 5	13.82

Specifically, we find significant evidence artists who function as a bridge between historical cohorts (Sequence 1) and those who fit with previous, established artists (Sequence 3) are significantly better recognized in art historical texts than other artists in our population.

7. Discussion and conclusion

This research finds five network types in which artists are historically positioned within Dutch museum exhibitions. Some types are anticipated, such as Sequence 5, which captures those ephemeral artists who, despite promise, disappear from exhibition—as the majority of personages disappear from the historical record. Sequences 2 (“slow-starters”) and 4 (“sporadic”) capture inconsistent historical connections, demonstrating an unsettled, uncertain placement in history. Over the course of 40+ years of exhibition, curators found it difficult to create lasting connections in which to position these artists within a historical context. Of the five sequences, Sequence 1 (“bridges”) and 3 (“retrospectives”) demonstrate the most consistent historical networks over the timeframe, albeit in different ways. While Sequence 1 forms consistent connections to cohorts from a broad historical base (past, contemporary, and future), Sequence 3 shows consistent connections between artists who had previously established themselves in exhibition (i.e., “past”).

Though different types, it is important to note both Sequence 1 and 3 demonstrate a more consistent narrative of connections than the other network types in this research. And, as we hypothesized, a consistent narrative is important for historical commemoration. If history is established relationally, then generations need to be presented building on the advancements of the former and, in turn, impacting those following. Such progression narratives are particularly clear in art history, where an evolutionary course is often drawn between historical cohorts and leading to the next avant-garde. Our analysis demonstrates that those artists who have the clearest historical contextualization receive the most historical commemoration. Note, though, a sequence type for artists who are connected to chronologically subsequent artists (“future”) did not emerge. This finding suggests retrospective commemoration, where a past artist is revered for his or her connection to a current movement (see, for example, [Corse and Griffin, 1997](#); [Lang and Lang, 1988](#)) is not a common phenomenon, at least within our exhibitions. Rather, artists who are rooted in connections with past artists tend to receive greater commemoration, suggesting lineage plays an important role in evaluating artistic significance.

The research presented here has three main objectives. First, we are interested in exploring the idea of historic networks, which we define as connections created by others (rather than by the actor her or himself) with the intent of positioning an actor within a historical context and cohort. In this research, we examine how historic networks influence commemoration through recognition within art historical texts. With our second objective, and counterpart with the first, this research explores the institutional advocacy of historic networks through museum exhibitions. While explicit, often celebrated connections may anecdotally connect artists (such as collaborations or friendships), we argue these are often not the connections that serve the majority of artists. Rather, numerous connections created over time by a variety of reputational entrepreneurs (e.g., different curators) culturally embed associations that implicitly occur through shared exhibition space—thereby, forming a multidimensional historical contextualization. Exhibition connections create a historic network that place artists within the connective tissue of history. As museum exhibitions mediate the artist, moving her or him into the public domain, they become the building blocks of recognized art history. If the atelier or studio is the place where artists create works, “exhibitions are the sites where such creations meet the public and, in the course of their reception, make, and re-make, art history” ([Reiner and Patkowski 2013:8](#)).

Finally, we present historic networks as a type of symbolic network, i.e., a network created by others to associate two actors as a means of influencing how an actor is understood. In the present research, we examine historic networks as a tool of history-building. Yet, the idea of historic networks can be more widely applied, specifically in areas where reputation is salient. We suggest historic networks can be extended beyond their use in this research in at least two ways. First, this research only examines connections created through a specific institutional medium, museum exhibitions. However, we believe there are numerous means through which important others create historic connections, such as through critical evaluations, peer categorization, prize or award groupings, compilations and anthologies—to name a few possibilities.

Second, our study focuses on historical connections. Yet, we believe there are several dimensions on which symbolic networks may be created, such as genre, geography, race, and gender. Indeed, the interplay between social and symbolic networks may work in the creation of reputation. Finally, while in this research we focus on the quantitative dimension of connections in a network, an understanding of the qualitative reasoning behind connections, and how these narratives resonate with audiences, is needed.

The development of history is the development of connections. In creating a narrative progressing the past into the present, and envisioned future, historians work to associate and connect historical figures. While we think of historians elucidating the explicit connections between actors, to see this as the whole of history-building is to miss the implicit conceptual work intersecting cohorts and creating history's narrative flow through time. Though the narratives of history are heterogeneous, with a plurality of voices each trying to be heard, we find aggregated historical associations provide clear indication of historical contextualization. This article shows only one of the ways in which networks function in the shaping of reputation and narrative in a specific field. Empirical extensions towards different fields, with different functions of reputations, and theoretical extensions towards the nature of connections and the dimensions on which they are placed, promise valuable research on the effects of perceived relationships on individual success.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.poetic.2020.101446](https://doi.org/10.1016/j.poetic.2020.101446).

Appendix A

Our definition of an artist's "strong connection" to a particular cohort within a given timeframe assumes that the strength of connections is relative: the absolute number of connected artists through exhibitions matters, but only in comparison to other artists exhibited in that timeframe. With that assumption, the question arises how "strong" a "strong connection" is. In this research project, we define a connection to be "strong" by comparing it to the most-connected artist within a specific time frame: if an artist has (over) 50% of the connections that the strongest-connected artist had within that given time period, we consider that artist strongly-connected.

The decision of this 50% cut-off point is grounded in the empirical data. As the cut-off point determines the distribution of artist's states within each given period, we needed to select a point that allows for differentiation between the artists and their sequences. To select our ideal cut-off point, we calculated the ratio between the number of "highly connected" and "weakly connected" states that arise with a given cut-off point. Fig. A1 shows the ratios for every possible cut-off point. When this ratio nears 1.00, this means the number of "strongly" and "weakly" connected states is equal—which is the distribution most desirable for our analysis. In this graph, we see that the line nears 1.00 between 48 and 50%. To allow for theoretical interpretation, we then opted for the cut-off point of 50%, as this offers easier interpretation: a strong connection means that an artist is connected to a particular cohort half as strong, or more, as the best-connected artist.

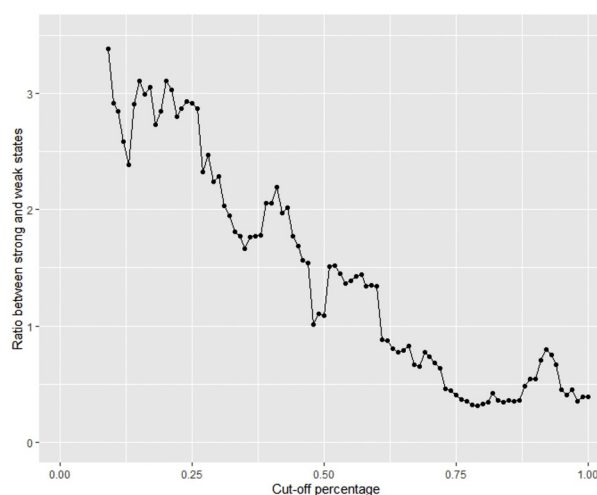


Fig. A1. Ratios of "Strong" and "Weak" states per percentage cut-off point

Appendix B

Optimal Matching methods allow researchers to discern patterns of similarities between units in a given dataset (McIndoe and Abbott, 2004). As our objective now is to group artists together based on the sequence of network positions they occupy, we use an Optimal Matching algorithm to uncover how similar or dissimilar artists' sequences are from one another. Based on these similarity scores, we then group artists together who are most alike (and dislike the other artists). In this appendix, we describe the choices we made to program our OM algorithm. As Table B1 illustrates, some sequences are alike, while differing strongly from others. For example, the sequences of the artists Constant and Corneille differ only at one point in time, while the remainder of their sequences are equivalent. In contrast, the sequences by Marinus Boezem and Dieter Roth substantially diverge.

Optimal Matching uncovers underlying patterns in the sequences by calculating how "costly" it is to transform one sequence into another. There are three operations the OM algorithm employs: altering one state in the sequence into another (e.g., changing an A score into a B), deleting a state, and inserting a state. To illustrate, transforming the sequence of Constant into that of Corneille requires only one transformation (i.e., changing A into F at moment 3). In contrast, transforming the sequence of Marinus Boezem to

Table B1

Example of sequence fragments for illustration of equivalency and differences

Artist	1	2	3	4	5
Corneille	F	H	A	A	F
Constant	F	H	H	A	F
Marinus Boezem	H	G	X	H	E
Dieter Roth	F	H	X	H	E

Table B2
Transformation cost matrix

	A	B	C	D	E	F	G	H	X
A	0	1.8	1.95	1.67	1.92	1.71	1.94	1.53	1.95
B	1.8	0	1.97	1.78	1.81	1.8	1.94	1.51	1.69
C	1.95	1.97	0	2	1.67	1.83	1.83	1.66	2
D	1.67	1.78	2	0	2	1.95	1.94	1.88	1.78
E	1.92	1.81	1.67	2	0	1.95	2	1.75	1.43
F	1.71	1.8	1.83	1.95	1.95	0	2	1.56	1.84
G	1.94	1.94	1.83	1.94	2	2	0	1.42	1.81
H	1.53	1.51	1.66	1.88	1.75	1.56	1.42	0	1.24
X	1.95	1.69	2	1.78	1.43	1.84	1.81	1.24	0

be identical with Constant is more “costly,” requiring five operations to achieve equivalency.

Comparing two sequences, OM assesses for which values and at which positions in the sequence a transformation must occur for equivalency. However, not all operations are equally impactful, as some sequence states are closer to one another, while others differ more markedly. For instance, score E (indicating strong connections to “past” cohorts) and score G (indicating strong connections to “future” cohorts) are theoretically antitheses, while scores G and H (where H is weak connections to any cohort) are more closely related. All such possible transformation combinations have specific costs, which the program retrieves from a cost matrix. Traditional OM methods are based on manually created cost matrices, where the researcher determines what values differ more from others and ascribes a certain “cost” to a transformation from one state into another. [Abbott and Tsay \(2000\)](#) note the researcher’s determination of these scores is problematic. Consequently, we opt for an alternative grounded in our empirical findings, proposed by [Gabadinho et al. \(2011\)](#). Transformation costs are thus based on differences found in the data, rather than by predefined values, which are arguably distinct from empirical reality.

We base our cost matrix on probabilities. In this matrix, the transformation costs between two values in a sequence is based on the actual probability of one state temporally following the initial state. As such, if value B is very likely to follow value A, the transformation costs of B into A will be low, while a very rare shift of states (i.e., an A following an X) results in higher costs. The transition costs ω from i to j , for every case in which state i is not state j are calculated:

$$\omega(i|j) = 2 - p(i|j) - p(j|i)$$

Here, $p(i|j)$ is the transition rate of state i into state j . As $p(i|j)$ can be a maximum of 1 (all states i are followed by j) and a minimum of 0 (never is i followed by j), the costs in the cost matrix theoretically range from 0 (these two states *always* followed one another, therefore being “cheap” in a sense of transformation) to 2 (these two states *never* change into each other, thus being the most expensive transformation). The calculated cost matrix can be found in [Table B2](#).

In addition to transformation costs, the OM algorithm has an alternative operation of inserting or deleting a specific score into a sequence. These “indel” costs are included in the algorithm to ensure the program recognizes sequences that are similar yet start or end at a different point in time. We follow the advice of [Aisenbrey and Fasang \(2010\)](#) and the empirical example of [François and Dubois \(2013\)](#), who consider half of the highest possible transformation cost (2) to be the most appropriate score. Therefore, in our analysis, the indel cost is 1.

We apply this cost matrix to all possible combinations of sequences to calculate how distinct two sequences are from each other. This results in a “distance matrix” containing scores indicating the difference between sequences. Higher scores in this matrix express high transformation costs between two artist’s sequences, signaling they have dissimilar trajectories through exhibition positions. The distance matrix provides information on each artist, which then allows us to group artist together based on sequence similarity.

Using Hierarchical Clustering to find the “cheapest” way to divide the set of sequences into groups, we calculate underlying structural types using [Ward’s \(1963\)](#) minimum variance method. Calculations are done stepwise: first, finding the sequences which minimally differ (e.g., Constant and Corneille in [Table B1](#)) and grouping them together. The closest sequences to this group is then ascertained and added. Using the cost matrix to calculate the cost of changing an individual sequence into another, we group sequences together based on the process that costs least in total transformation—that is, any other choice of typical sequences would be more costly. To analyze the distinctiveness of the emerging sequences, we execute a paired samples t-test to compare the differences of transformation costs within and between clusters. A division into five different sequences yields significant results ($t(235) = -33.99, p < 0.001$).

A seven-sequence division also provides significant differences in transformation costs ($t(235) = -45.41, p < 0.001$), although the two subsequent sequences further divided do not differ in theoretical interpretation. Particularly, with a seven-sequence division, we find Sequence 3 becomes two groups with very similar exhibition connections, yet at different time points, and Sequence 5 becomes two “ephemeral” groups that differ only at the moment of entering museum exhibitions. Given these results, we have chosen for five-division sequences.

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